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From organizational capabilities to corporate performances: at the roots of productivity slowdown

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Abstract

This paper is one of the first attempts at empirically identifying organizational capabilities—in this work concerning Italian firms. Together, it proposes new evidence on the link between capabilities and economic performances. To this aim, we employ the *Indagine Multiscopo del Censimento Permanente delle Imprese* (IMCPI), a survey carried out by the Italian Statistical Office (ISTAT) in 2019, covering the three-year period 2016–2018, addressing a wide range of organizational characteristics including various organizational routines, human resource management (HRM), internationalization strategies, and many others. Our contribution is threefold: first, we aim at detecting what practices and combinations of them result in underlying different capabilities; second, we propose a taxonomy of the production system, both at firm- and sector-level based on the mapping of such capabilities; and third, we study the performance outcomes of different capability taxa in terms of productivity growth.

JEL classification: D21, D22, D83, J24, J53

1. Introduction

How do firms do what they do? And how effective are they in such activities?

A growing literature has addressed these questions by pointing at the nature and dynamics of firm-specific capabilities (Amit and Schoemaker, 1993; Dosi *et al.*, 2000, Helfat and Peteraf, 2003; Dosi *et al.*, 2008; Helfat and Winter, 2011). Firms are more or less complex organizations that, in order to reach their objectives, set up a series of procedures calling them *organizational routines* and *heuristics*. The procedures— aimed at building an artifact— entail the acquisition of inputs of production, the transformation of the inputs along the production process, the process of hiring new personnel, and the implementation of forms of learning on-the-job and training schemes. However, firms do not only perform ordinary procedures but are also the locus of new knowledge generation. This requires search and discovery activities, which may be performed inside or outside firm research and development (R&D) departments. Whenever R&D processes are successful, new innovations, entailing new products, or methods of production are brought to the industrialization phase. All these activities require relational processes with external actors, ranging from suppliers to financiers. Finally, firms have to face markets and therefore require heuristics, e.g., to set prices and open new commercialization opportunities for their products. All these procedures are inbuilt in the *procedural knowledge* upon which organizations strive and, when possible, expand.

Organizational capabilities are the collective manifestation of the ensembles of these procedures. Spotting within organizations the exact segment or function in which such capabilities exactly lie is a tall and futile task. Organizational capabilities are in fact the result of the *combinations* of specific routines and heuristics and are seldom decomposable in the contribution of single activities (Simon, 1991a; Marengo and Dosi, 2005). If any, the analytical task at hand should focus on the identification of the properties of *different combinations* of such organizational routines and heuristics.

Equally difficult is detecting how the firm's internal organizational structures and capabilities map into its external performance. The same question can be formulated using a biological metaphor: how does the *genotype* of the firm, i.e., the ensemble of its organizational capabilities, reflect in the revealed performances of the *phenotype*? Addressing this issue requires to go beyond standard sources of firm performance, such as size, access to international markets, and more recently age, and to study the actual link between *how firms do things* and *how they perform*.

It is important to notice that the distinction *genotype* vs *phenotype* in the social domain should not be taken literally, as it is much more blurred than in biology. So far, in human organizations, their quasi-genetic traits (Cohen *et al.*, 1996) essentially coincide with their *recurring action patterns*. Therefore, to identify capabilities in a non-tautological way—i.e., firm "x" embodies great capabilities because it displays outstanding performances—researchers should firstly identify such action patterns and later try to map them into performances. And this is what we shall do in the following, by making use of a unique and innovative firm-level dataset, the *Indagine Multiscopo del Censimento Permanente delle Imprese* (IMCPI). The IMCPI was carried out by the Italian Statistical Office (ISTAT) in 2019, and it covers the period 2016–2018 and addresses a wide range of firm organizational routines and heuristics—concerning, e.g., hiring practices, human resource management (HRM), price-setting rules, software-aided decision methods, position in the market vis-a'-vis suppliers—and strategies—e.g., regarding internalization, new product development, and new investments in advanced technologies.

In our analysis, we first match the qualitative information afforded by the IMCPI with quantitative balance-sheet data on firm performances. Secondly, we undertake a factor analysis on the behavioral traits and strategic orientations of the firms. By using a K-means algorithm, we identify four clusters of firms in terms of the co-occurrence of firm strategies and characteristics that we denominate the *Essential*, *Managerial*, *Interdependent*, and *Complex* cluster. We map such clusters into performance variables, in particular by looking at labor productivities, wages, employment absorption, and the dynamics thereof.

First, our findings show that organizational capabilities, our "state" variables, are more important in determining firm performances than managerial practices, our "control" variables.[1] In line with our interpretative conjectures, we do not identify a unique and dominant set of *best practices*, while we do find strong complementarity between different organizational practices. Indeed, the best performers are the firms able to develop more complex behaviors—i.e., those able to implement a variety of actions with respect to a given purpose, such as digitalizing the organization. Higher organizational complexity—captured by the range and variety of actions put in place by firms—is thus reflected in better performance. Moreover, together with organizational capabilities, also managerial skills and relational patterns – both external (i.e., with suppliers in terms of

[1] Hereby, the notion of state vs control variables has to be intended in the words by Winter (1998), according to which state variables represent inner firm characteristics relatively invariant, while control variables are those for which managerial choices can influence the direction of the organization's evolution.

orders, contracts, and R&D acquisition) and internal (with the firm's workforce)—are crucial in explaining factor variance.

Second, the proposed econometric estimations of the different dimensions of firm performance, carried out both in levels and growth rates, reveal that belonging to the *Interdependent* and *Complex* clusters considerably increases firm performance in terms of labor productivity. Notably, *Complex* firms are also strongly characterized by a neater labor-absorbing attitude. The estimations, robust with respect to the introduction of size, age, exporting status, and other fine-grained control variables, highlight diverging growth patterns in productivity between the "low-level" clusters—Essential and Managerial—and the "high-level" clusters—Interdependent and Complex firms. With the aim of controlling for potential size effects, that at a first glance might be mistaken for complexity attributes, we also perform the analysis by subsamples of small, medium, and large enterprises.

Differences in capabilities, as captured by the taxonomies introduced earlier, not only appear to be crucial determinants of widely heterogeneous corporate performances but are also likely to be instrumental in accounting for the contemporary dynamics and distributions of industrial productivity. Italy, in this respect, is an extreme case to the point.

The stagnation of Italy's productivity has deep roots and has been observed since the beginning of the 2000s (Daveri and Jona-Lasinio, 2008; Calligaris *et al.*, 2016). However, productivity stagnation does not appear to be an Italian only phenomenon, but an emerging trait of the current phase of contemporary capitalism. A trait that has become even more pronounced after the 2008 economic crisis (Foster *et al.*, 2016; Syverson, 2017) and has most likely been affected by the COVID-19 pandemic downturn, adding up to the longer-term microeconomic evidence pointing at considerable heterogeneity in firm productivity levels. Few high-performance firms coexist with a large population that exhibits modest and stagnant levels of value added per worker, regardless of the degree of sectoral disaggregation (Dosi *et al.*, 2012). These results suggest the emergence of "neo-dual" or "winners take the most" configurations, featuring a productive structure increasingly quasi-dichotomous in terms of organizational skills, technological innovation, and presence on international markets. A dichotomy that is mirrored by a progressive divergence in performance (Dosi *et al.*, 2021) on which dimensional, rather than sectorial, aspects appear to have a significant impact. However, size is not the only possible explanation: there are indeed small firms recording increasing productivity trends (Monducci and Costa, 2019; ISTAT, 2020), especially the productive units that invest in technology and worker abilities (ISTAT, 2019) or that successfully operate on an international scale (Costa *et al.*, 2017; ISTAT, 2017).

The contribution of this paper is threefold: first, it empirically operationalizes the notion of firm-level capabilities; second, it identifies robust taxonomies thereof; third, it provides an interpretation of the productivity slowdown based on the inherent organizational structures of the firms. In doing so, our analysis introduces a novel and crucial dimension for interpreting the evidence on the emerging neo-dualism in productivity levels and on the slowdown in productivity growth: high-capability firms, the main drivers of industrial dynamism, might be a small, and possibly even shrinking, minority. The Italian productive structure is in fact populated by a large fraction of *Essential* firms, while *Complex* firms represent only the 9% of the population of enterprises with at least 10 employees.

The analysis also bears some macro-developmental implications in so far as capabilities impinge also upon the introduction of new products, practices, and techniques of production. Our micro evidence may therefore be seen as complementary to the broader macroeconomic literature that has identified product and sector *diversification* as determinants of economic development (Dosi *et al.*, 2021; Sbardella *et al.*, 2018; Tacchella *et al.*, 2012).

The remainder of this paper is organized as follows. Section 2 discusses the notion of organizational capabilities. Section 3 describes the dataset and presents the structure of the IMCPI questionnaire. Section 4 develops a capability-based taxonomy of Italian firms. Section 5 corroborates the descriptive evidence obtained in Section 4 with an econometric analysis. Section 6 concludes.

2. Organizational capabilities

To define what an organizational capability is, we rely on Helfat and Winter (2011) definition, according to whom:

- the possession of a specific capability requires that an organization or its constituent parts have the capacity to perform a specific activity in a reliable and at least minimally satisfactory manner;
- a capability has an intended and specific purpose, e.g., the capability of building a car;
- a capability, differently from an ad hoc activity that does not reflect predicted or patterned behaviors, enables the repeated and reliable performance of a procedure.

Firms, in their hierarchical structure and functional division, are the loci of continuous and evolving learning, and their performance is driven by highly idiosyncratic technological and organizational capabilities grafted on their procedural knowledge—who does what, who sends a signal, and to whom, what should be done in case of errors, etc. (Winter, 1998; Dosi and Nelson, 2010). Complementarity in the use of inputs and in organizational forms is the norm rather than the exception. Alternative knowledge configurations are present at all levels of the organization, from R&D divisions to assembly lines, and are associated with different innovation regimes—in terms of new products, processes, and practices. Organizational routines represent the *trait d'union* between technology and business organizations: in this perspective there are no unique "optimal" configurations of organizational practices that lead to maximizing performance metrics (Dosi and Marengo, 2015).

Firms—and more in general any type of organization—ought to be understood as *behavioral entities*, relatively inertial over time and tolerant of errors (Simon, 1991b). Organizational forms, technological practices, business cultures, and learning processes result in hybrid configurations: lean/agile and Taylorist archetypes (Vidal, 2017) are two examples. If the firm is a collective problem-solving entity, knowledge does not lie in individual know-how: therefore, individual practices of command and control may completely miss the goal of monitoring deviations from expected outputs. Technological and organizational capabilities are gradually built up and show a high degree of persistence in their quality (*good* versus *bad* practices). The heterogeneous set of idiosyncratic organizational capabilities leads to ample degrees of heterogeneity in firm characteristics and economic performances.

The literature further distinguishes between *ordinary* capabilities, roughly measuring the ability to do "business as usual", and "dynamic capabilities" broadly meant as the ability to fruitfully *alter* the usual way of proceeding (Teece *et al.*, 1997; Winter, 2003; Pisano, 2017). Four aspects are fundamental in understanding organizational capabilities. *First*, in a changing and evolving world, the distinction between ordinary and dynamic capabilities is inevitably blurred and, if pushed too far, might be interpretatively misleading. *Second*, both types belong to the "quasi-genetic traits" of the organization, are relatively sticky and path-dependent, and in the short-term only limitedly subject to the discretion of strategic management (see Pisano, 2017 for a discussion on the thorny issue of managerial discretion with respect to organizational capabilities). *Third*, as emphasized by Helfat and Winter (2011), capabilities are a matter of degree, ranging from minimally satisfactory to exceptional. *Fourth*, capabilities, as already emphasized, have a *procedural nature*, i.e., they are the collective organizational equivalent of "playing well the violin in an orchestra"; hence, they are intrinsically different from strategies and endowments.

The study of the impact of organizational forms upon performances is not novel. The literature has investigated the impact on innovation or labor productivity of, e.g., the application of internal labor market practices—such as high-performance work (HPWP) or human resource management (HRM) practices, defined in terms of continuous improvement processes, team meetings and teamwork, workforce rotations, career advancements, or decentralized decision-making processes. Prennushi *et al.* (1997) focus on US steel finishing lines and study the effects of such practices on labor productivities. Ichniowski and Shaw (1999) compare the effect of the adoption of Japanese HRM practices between US and Japanese firms. Koski *et al.* (2012) study the impact on innovation outcomes in Finnish manufacturing firms. Osterman (2006) looks at the effects on wages, and Cappelli and Neumark (2001) analyze the effects on both labor cost and labor productivity. Notwithstanding the differences in the foregoing studies, they share a strong emphasis on the relevance of *complementarity* and the absence of a unique best-performing organizational model.

It is revealing to compare this theory with other approaches that view observed strikingly heterogeneous firm performances—in terms of productivity, profitability, sales, or employment levels—as entirely driven by managerial actions. The standard views of firm performance in economics, to which we refer to as the *best managerial practices* approaches, are deeply rooted in the production function paradigm and in contract theory. In this perspective, management comes before organizational routines, and performances can be traced back to the levels and dynamics of production inputs. Managerial abilities, rather than organizational routines, are, in this view, the key drivers of performance heterogeneity, and therefore the firms adopting the best managerial practices are expected to perform better. Managerial functions must entail (i) monitoring behaviors, (ii) defining incentives, and (iii) setting targets or objectives. Best practices should thus include the ability to define monitoring processes—i.e., taking action in case of errors—as well as the capacity to reward (punish) behaviors that are (not) in line with defined targets.

This view is shared across several approaches, with diverse focuses, ranging from contributions addressing workers empowerment to studies more interested in assessing the efficiency of management systems—e.g., see among many others Piore and Sabel (1986), Bloom and Van Reenen (2007), and Bloom *et al.* (2012). For instance, by relying on telephone questionnaires administered to firms in various countries and sectors, Bloom and Van Reenen (2007) look at the presence of specific sets of managerial practices and their impact on productivity. These practices are interpreted as direct expressions of managerial strategies and include the definition of individual incentive schemes and systems to control the performance of individuals and processes. The emphasis on rewarding and punishing devices, and thus on monitoring the work process, reveals a Taylorist vision of the organization, in which the real organizational levers are command and control, albeit at times mitigated by forms of de-hierarchization and autonomy (echoing Adler, 1993). In this top-down approach, rather than being a unit coordinator, the manager becomes a motivator/controller that rewards or punishes subordinates through continuous control processes. An example reported by Bloom and Van Reenen (2006) of a *best managerial practice* describes a US firm manager that promptly removed the organization's dead spots by firing four people in few months and stating that: "We move poor performers out of the company or to less critical roles as soon as a weakness is identified" [p. 477].

The capability-based view is clearly very different, even if, admittedly, with empirical predictions much more difficult to detect as one cannot look for single "best strategies" but rather for combinations of organizational procedures. This is precisely what we shall look for in the following.

3. From theory to empirics: mapping firm *genetic traits*

Let us begin with an overview of the data (Subsection 3.1), describing in some detail the structure and organization of the questionnaire. Next, in Subsection 3.2, we proceed with a factor analysis to reduce the high dimensionality of information, as a first step toward the identification of taxa of capabilities/firms.

3.1. Dataset overview and methodology

Over the last 20 years, the demand for high-quality firm-level micro-data has increased significantly, both for the purpose of measurement of economic phenomena and for policy reasons. In this context, the Italian statistical agency ISTAT has undertaken the design of a new generation of micro-founded statistics, in which the microeconomic component plays a central role. This new approach is based on the implementation of a twofold integrated strategy in statistical production:

a) the massive use of administrative data for the construction of multidimensional statistical registers, with extensive possibilities to link individual data to additional administrative sources and direct surveys;

b) direct statistical surveys focused on economic units with multi-purpose modules able to measure their organizational structures, behaviors, and strategies, not detectable when using administrative sources only.

The first wave of the IMCPI was carried out by the ISTAT in 2019, collecting information about Italian firms' behaviors and strategies in the three-year period 2016–2018. The survey involved a sample of about 280 thousand firms with 3 or more employees, representing a universe of over 1 million units, corresponding to the 24.0% of total Italian firms, that however account for the 84.4% of national value added and employ the 76.7% of workers (12.7 million) and the 91.3% of employees.

The questionnaire administered to firms is structured along nine macro-sections: (i) Ownership, control, and management; (ii) Human resources; (iii) Relations between companies and other organizations; (iv) Market; (v) Technology, digitalization, and new professions; (vi) Finance; (vii) Internationalization of production; (viii) New trajectories of development; and (ix) Environmental sustainability, social responsibility, and workplace security. The integration of qualitative information derived from the survey with administrative registers—the structural business statistics drawn from the *Frame-SBS* dataset—enables in-depth analysis of the structure, behavior, and performance of Italian firms, and is particularly useful in examining productivity dynamics.

In the following, restricting the scope of the analysis to firms with at least 10 employees to ensure a minimum firm-organizational structure, we obtain a sample of more than 109 thousand units, representative of a universe of about 215 thousand firms, with 9 million workers (54.7% of the total), of which 8.8 million are employees (74.7%), with 2300 euro billion revenues (75.3%) and 557 billion (71.4%) value added. Within this segment, there are approximately 3700 large firms (250 or more workers), with employment and value-added shares of 38.5% and 44.8%, respectively. Small and medium enterprises (SMEs) (10–249 workers) thus constitute the majority of structured Italian firms in the main macro-sectors (including manufacturing and services), not only in terms of employment but also in terms of value added.[2]

Based on the analysis of the IMCPI dataset, our empirical strategy rests on the following multi-step procedure.

1. Factor analysis on the IMCPI questionnaire answers by firms—we perform a dimensionality reduction of the variables identified as relevant to define the behavioral traits of the firms. The factor analysis is conducted twice: first at the level of the questionnaire macro-sections (seven out of the nine thematic domains described above) yielding one factor per section (seven factors) and second we further reduce the dimensionality across macro-sections and move from seven to three factors.

2. Clustering of firms by factor intensity—we perform a K-means clustering analysis across the entire sample of firms and identify four clusters on the basis of the factor loadings.

3. Analysis of the co-occurrences of organizational capability combinations—by performing a χ^2 test, for each cluster we identify the co-occurrences of the combinations of practices and strategies in the questionnaire answers by the firms belonging to the cluster.

4. Link between firm organizational capabilities and performance—we characterize each cluster in terms of performance variables and sectoral distribution, relationships that will be then also examined through a set of econometric tests in the second part of the empirical analysis.

3.2. Factor analysis

The IMCPI, especially thanks to its process-centered features, is particularly apt to investigate the characteristics of Italian firms through the lenses of the capability theory of the firm outlined above.

As mentioned, we adopt a data-driven, multistep approach. First, we select a subset of items that cover the most distinctive operational attributes of firms and that we consider to be relevant and in tune with a capability theory of the firm. The selected items range from questions

[2] The same dataset was recently employed in other related works, see among others Calvino *et al.* (2022) and Costa *et al.* (2022a, 2022b).

Table 1. Selection of 40 questions from the IMCPI (2018). Questions flagged with X represent nested alternative practices

1.	**Ownership, control, and management**	5.	**Technology, digitalization, and new professions**
X.1.3	Past strategic objectives and their outcome	5.1	Innovation activities (internal or through external suppliers)
X.1.4	Future strategic objectives	5.3	Use of digital platforms
2.	**Human resources**	X.5.7	Use of business management software
2.1	Acquisition of new human resources	X.5.8	Software for business management functions
2.2	Type of human resources acquired	X.5.9	Use of cloud services
X.2.3	Methods of selection of human resources	X.5.10	Type of cloud services used
X.2.4	Functional areas where human resources have been acquired	X.5.12	Past and future investments in digital technologies
2.5	Most important transversal skills in the selection of human resources	X.5.14	Type of training for technology adoption
X.2.7	Personnel management practices	X.5.15	Relevant digital skills adequately possessed by personnel
2.8	Practices to attract and/or retain qualified personnel	X.5.16	Future change in the share of personnel dedicated to digitalization tasks
2.9	Non-compulsory corporate training activities	5.17	Methods for dealing with future management consequences
X.2.10	Type of non-compulsory training		
X.2.11	Compensation subject to non-compulsory training activities		
3.	**Relations between firms and other entities**	**8.**	**New trajectories of development**
3.1.	Relations with other firms (orders, contracts, subcontracts, etc.)	8.1	Past and future areas of specialization
3.2	Parties with whom relations have been initiated (in Italy or abroad)	8.4.1	Type of enabling technologies produced
X.3.3	Functions of relations with other firms	8.4.2	Enabling technologies used to innovate processes, goods, and services
3.4	Relation reasons	8.5.1	Past investment intensity
X.3.8	Sectors of the firms with which relations have been maintained	8.5.2	Future intensity investments
		8.7	Services purchased by the firm
		8.9	Development processes undertaken
4.	**Market**	**9.**	**Environmental sustainability, social responsibility, and safety**
X.4.5	Criteria for setting goods or services prices in the reference market	8.9	Measures to improve work well-being and ensure equal opportunities
X.4.7	Strengths	9.10bis	Measures to support parenting and work–family balance
		9.18	Actions undertaken to ensure work safety

on ownership structures, personnel management practices, relations with other firms within the supply chain and customers, market relations, technological set-ups, future investments, and development prospects, to social relations, workforce safety and well-being. More in detail, we focus on subsections of the survey belonging to the seven macro-areas: *Ownership, control, and management; Human resources; Relations between firms and other entities; Market; Technology, digitalization, and new professions; New trajectories of development*; and *Environmental sustainability, social responsibility, and safety*. After our informed selection, we retain 40 questions. Table 1 reports the selected questions for each of the thematic macro-area of the survey.[3] The whole questionnaire structure is presented in Appendix A, with reference to the selected

[3] The contents of Sections 6 and 7 of the IMCPI—including specific aspects of firm–bank relationships and firm offshoring—have not been considered in our analysis because they were not in line with the purpose of identifying firms' organizational and technological capabilities.

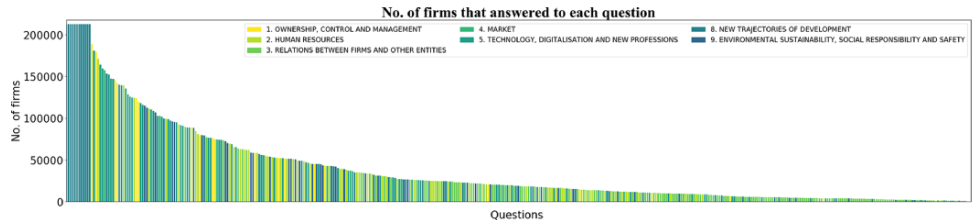

Figure 1. The response rate of the examined questions

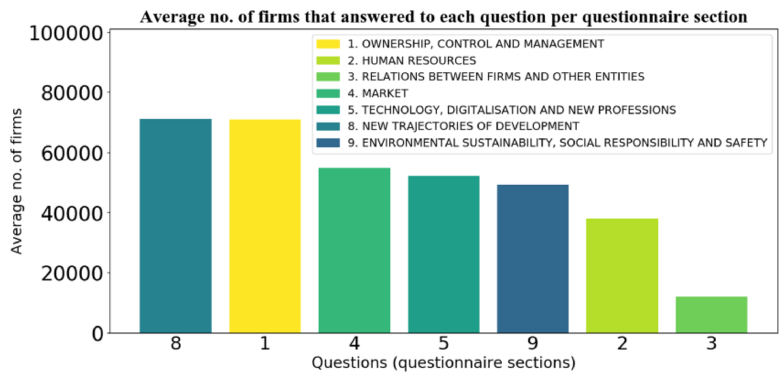

Figure 2. The average number of answers to the questions examined in the analysis

questions, including the demand formulation and the potential replies, whether multi-outcome or dichotomous.

A descriptive analysis of the response rate suggests strong heterogeneity in the examined questions. The long tail of the distribution in Figure 1 shows that in general the response rate is higher in questions of a simple nature (yes/no) and gradually decreases as the complexity of the question increases. This hints at the corresponding dominance of simple behaviors. Figure 2 displays the average response rate to the questionnaire per section. Indeed, the nature of the information extracted in each section is different, as it is the degree of complexity of the underlying actions. The selection of the questions reflects the search of firm characteristics in terms of *state variables*—i.e., relatively invariant structural characteristics of the firm—and *control variables*—attributes of the decisional-managerial dimension, e.g., business strategies.

As a second step, given the high dimensionality of the information, we carry out an analysis of multiple correspondences in the set of selected questions. By operating a dimensionality reduction, we extract seven latent factors that summarize the informative content of each of the seven subsections taken into consideration.

More in general, the complexity of the questionnaire (cf. Section 3.1) directly affects the overall data analysis strategy. A global analysis of a highly heterogeneous set of variables does not necessarily produce useful synthetic dimensions. In contrast, the prior selection of a coherent subset of dimensions ("themes") allows deriving synthetic and structural indices (the first principal component of each theme), which, in turn, reflect some latent, unobservable combinations apt to express the "behavioral" attributes of a given population. These synthetic indicators represent informative partial syntheses *per se* but can also be used as a basis for the subsequent overall analysis (Bolasco *et al.*, 1990). In particular, we rely on an unweighted multiple-factor analysis, a set of techniques widely used in different disciplines (Pagès, 2002). We apply the unweighted analysis since all dimensions have comparable variances, thus the structure of the questionnaire is not dominated by any group of variables.

As a first step of our multivariate analysis, we perform seven preliminary partial dimensionality reductions, one for each of the following questionnaire macro-sections: *Ownership and management; Human resources; Inter-firms relations; Market strengths; Technology, digitalization, and* *innovation; New development paths*; and *Sustainability*. The seven indicators, associable with seven organizational-strategic profiles describing ensembles of behavioral attributes of Italian firms, are reported in Table 2. Nearly all the factors account for a high portion of total variance, as captured by the principal inertia indicator in Table 2, thus proving to provide an effective and satisfactory synthesis of the multidimensional IMCPI macro-areas. Next, to further synthesize the information contained in the questionnaire, we perform a factor analysis on these initial seven factors and obtain three latent factors that account for 69% of total variance. The sampling adequacy, which yields a Kaiser–Meyer–Olkin (KMO) test of 86% (thus above the 80% required threshold), confirms the robustness of this second factorization. These three factors are ascribable to different sets of capabilities. The first factor is linked to work organization, employee training processes, the presence of HPWPs, recruitment mechanisms, technological-organizational skills linked to investments in digitalization, the use of management software and platforms. The second factor concerns managerial strategies, in terms of both past and future targets, pricing and investment strategies. The third is connected to processes of external relations with other firms in terms of contracts or suppliers, and processes of internal relations with workers.

More in detail, Table 3a presents the three factors sorted by explained variance and main key variables related to each of them. Starting with the first factor, the weights (or factor loadings) of each of the seven sections of the questionnaire (see Table 2) are positive, with the three main weights deriving from the variables contained in the sections *Technology, digitalization and new professions* (0.80 factor loading), *Human resources* (0.75) and *Ownership, control and management* (0.73). This first factor, which we refer to as *behavioral complexity*, accounts for 46% of the variance in the answers to the survey and it is an indicator of the complexity of the firm's organizational capabilities. It combines traits attributable to firm organizational structure — i.e. the organization of work and the degree of digitalization—with elements that can be associated with pure managerial activity, such as investment strategies and business targets. We label this factor as *Technological-organizational capabilities*. The second factor, which adds a further 13% of explained variance, is predominantly determined by variables associated with managerial practices, in particular those contained in the *Market* section of the survey that concerns mainly market power and product quality (factor loading 0.80), *Ownership, control and management* (0.24), and *Environmental sustainability, social responsibility and safety* that provides information on internal company relations and shows a negative factor loading (-0.27). We label this factor as *Managerial strategies*. Finally, the third factor, which adds a further 10% of explained variance, thereby reaching a cumulative 69%, is determined by the relational variables or the information on the dependence/interdependence of the firm, in particular those contained in the sections *Environmental sustainability, social responsibility and safety* (factor loading 0.63), and *Relations between firms and other entities* (-0.56). We label this factor as *Relations*.

The factor analysis provides a number of relevant results. First, it is not possible to clearly distinguish between practices attributable to managerial strategies and those hinged on the organization's established practices. In fact, all variables that concern, e.g., training processes, learning mechanisms, problem-solving development, and team working are at least as relevant as the management strategic orientations in accounting for firm taxa. This implies that interpretations of inter-firm heterogeneity exclusively based on managerial practices are at best incomplete. Moreover, managerial visions and strategies cannot be put in place without sustained investments in technology, which represent a sort of pre-condition for their effective implementation. A second noteworthy remark is the apparent relevance of the structure of relations and interdependencies with clients, suppliers, and contractors, and of the ensuing hierarchy and positioning inside such a network of interdependencies. In this respect, our analysis captures the importance of the value chain fragmentation that a firm can alternatively dominate as a leader or be subject to. Finally, this dimension is also associated with the relevance of internal relations, especially with regard to work-life balance and workforce safety.

Table 2. Main characteristics of the factors

Indicators	Ownership and management	Human resources	Inter-firm relations	Market strengths	Technology, digitalization, innovation	New development paths	Sustainability
Principal inertia (%)	77.6	96.1	87.8	84.1	80.5	57.8	94.3
Number of variables	19	19	22	10	45	25	16

Table 3a. Organisational-strategic profiles of firms. Results based on the factor analysis conducted on the questions presented in Table 1.

Practices and Explained variance	Main key actions					
Technological-organisational capabilities (46%)	Staff training activities (for new recruits, or continuous training and retraining)	Investment in the workers' digital skills	Investments in advanced automation and interconnected machines	Investments in technology, digitalisation, R&D, and work organisation	Use of management softwares (ERP, CSM, SCM)	Use of remote management services (cloud)
Managerial strategies (13%)	Product quality as competitive strength	Market power (in setting the selling prices)	Expansion strategies (widening of the product range, extension of activities)			
Relations (10%)	Adoption of good practices for the staff professional development and equal opportunity protection	Adoption of measures for work-family balance (leave, furloughs leave, hourly flexibility)	Articulation of inter-company production relations (contracts, subcontracting, agreements)			

Table 3b. Firm clusters and organizational-strategic profiles (units with at least 10 workers), with three factors

		Organisational-strategic profiles		
		Technological-organisational capabilities	Managerial strategies	Relations
Cl1	Essential	14,2	69,8	62,5
Cl 2	Managerial	25,6	75,5	64,5
Cl 3	Interdependent	36,3	73,1	64,3
Cl 4	Complex	49,4	65,8	61,5
	Total	**27,4**	**72,4**	**63,6**

4. A behavioral taxonomy of the Italian firms and the mapping into their performances

To characterize the firms in our sample on the basis of the three latent factors obtained in the previous section, we apply a non-hierarchical algorithm for partitioning empirical data which yields the identification of four clusters of firms (see Appendix B for a more detailed description of the procedure). The number of clusters is selected using the Elbow criterion, with a total explained variance of 88%. Table 3b presents, for each cluster, the intensity of the three organizational-strategic profiles described earlier. The magnitude of the indices reflects how intensely the firms in each cluster are characterized by the behavioral attribute synthesized by each factor, vis-à-vis the firms belonging to other clusters. Reading the table by column, it is possible to appreciate a distinct pattern of monotonous growth of the first factor capturing technological and organizational capabilities, which are neatly sorted in ascending order moving from cluster 1 to cluster 4.

On the grounds of the first factor monotonic ordering we define the groups located at the two extremes of the index range as “Essential” and “Complex” according to Table 3b.[4] The other two intermediate clusters, in turn, are named according to the relative incidence of the measures that define them in a more specific way. In particular, we label firms in cluster 2 as “Managerial” since they show the highest value of the managerial strategy-related factor. Finally, we label “Interdependent” the firms belonging to the cluster 3, as they feature very high relational and technological factors, which hint at the possibility that those firms might be suppliers and having relationships with more complex firms.

Next, after studying the latent structure underlying the multi-purpose questionnaire, let us map what we defined as the “genetic” traits and the strategic orientations of firms into their performances. We use therefore a database that integrates the information from the IMCPI with that from the Frame-SBS business register. Table 4 presents some descriptive statistics about performance variables regarding the four clusters as measured in terms of labor productivities, profit margins and wages, and their relative frequencies. At a first glance, we observe that about two-thirds of Italian firms with at least 10 employees are Essential or Managerial—i.e., they belong to the first or second clusters—even though they contribute to less than one-third of the total value added. By contrast, the group of Complex firms in the fourth cluster, accounting for only 9% of the total universe, accounts for 42% of value added.

From a macro-sectoral perspective, in manufacturing, Complex firms are 12.8% of the total and account for 46.7% of value added; in market services, the ratio decreases to 7.8% of total firms and to 39.4% of value added. The observed patterns reveal first distinct differences among clusters in terms of size (21.2 average number of workers for Essential firms and 146.9 for Complex firms) and, second, remarkable macro-sectoral differences whereby advanced manufacturing

[4] There is a correspondence between the shape of the point cloud and the structure of the data in the matrix. The paraboloid shape of the point cloud (a frequent case in ISTAT qualitative surveys) corresponds to the so-called “Guttman, 1941 effect,” which highlights an arrangement of the row and column elements along a single continuum. This data structure reveals the existence of a relationship between variables and a unique dominant factor. Other successive factors are exponential functions of the dominant one (the second factor is a second-degree function, the third is a third-degree function, and so on): this is essentially the case of multivariate phenomena that express a single latent structural dimension.

Table 4. Characteristics of firm clusters (enterprises with at least 10 employees)

Cluster		Firm		Workers			Value added		Labor productivity (value added/workers)		Profitability (Mol/Revenues)[a]		Average salary (cost per employee)	
		Number	%	Number	%	Average	Total (euros Mln)	%	Average (euros)	Coefficient of variation	Average (%)	Coefficient. of variation	Average (euros)	Coefficient of variation
Cl_1	Essential	60,380	28.5	1,282,830	14.4	21.2	47,370.0	8.7	36,926	2.1	7.0	149.9	29,403.3	0.7
Cl_1	Managerial	77,040	36.4	2,106,065	23.6	27.3	1,03,816.5	19.2	49,294	1.1	7.4	60.9	34,714.9	0.5
Cl_3	Interdependent	54,267	25.6	2,595,343	29.1	47.8	1,59,340.2	29.4	61,395	1.3	7.9	3.5	40,543.2	0.4
Cl_4	Complex	20,070	9.5	2,947,326	33.0	146.9	2,31,373.3	42.7	78,503	1.4	10.1	35.8	49,655.7	0.5
	Total	211,757	100	8,931,563	100.0	42.2	5,41,900.0	100.0	60,672	1.2	8.7	73.0	40,434.8	0.5

[a]Mol: Gross operating margins.

firms, even if they are a small portion of the total, have a prominent role and contribute heavily to the overall value added.

Looking at the average productivity of each cluster, as measured by value added per employee, we observe that Complex firms are twice as productive as Essential firms (78 thousand and 36 thousand euros, respectively). Moreover, the intra-cluster variance is greater among Essential firms, with a coefficient of variation of 2.1 compared to 1.4 for Complex firms. In other words, the firms in the most productive Complex cluster not only do perform better but are also more internally homogeneous than the Essential ones. Additionally, we find a wide gap in average wages that increases by about 5 thousand euros, moving from the Essential to the Managerial cluster, and by 9 thousand euros from the Interdependent to the Complex ones. One may conjecture that higher average wages indicate more structured hierarchies and a higher number of layers in the firm, likely associated with larger size. However, as revealed by the intra-cluster coefficient of variation, the difference in average wages might well be due to a few firms with above-average remunerations but with comparable size and number of layers. In turn, this might be ascribable to firm wage–setting processes, which in Italy are also a result of the so-called second-level bargaining that might take place at the firm level on top of sector-wide national bargaining. Finally, conditional on larger average company sizes and higher productivity levels, the Complex cluster shows a stronger presence in international markets: more than half (54.2%) of the units of this group sells at least part of its products abroad compared to 16% in the Essential group.

These structural characteristics may also be detected by examining clusters by firm size. Let us consider two main classes, small enterprises (with 10–49 workers, Table 5) and medium and large enterprises (with over 50 workers, Table 6). A first common element to both dimensional classes is that average firm size progressively increases in the transition from the Essential to the Complex clusters. Note however that Complex firms show a limited, but non-negligible, presence (7.3%) in the small enterprise segment, while they constitute 25.8% of the medium and large enterprise one. Indeed, among small enterprises, there are about 14 thousand units with more complex profiles than three-quarters of medium and large enterprises. Labor productivity levels consistently reflect this pattern: a high-complexity profile appears to allow small firms to attain higher productivity compared to that of larger firms in the other three clusters. Despite having high wage levels, small Complex firms achieve also considerably high profit margins, lower only than those of medium- and large-sized Complex ones.

From a dynamic perspective, the clusters exhibit significantly different performances (Table 7). Between 2016 and 2018—a phase of expansion of the Italian economy—we observe a general growth in revenues, value added and employment, differentiated however according to the complexity of their practices. On average, labor productivity changes range from –0.2% for Essential firms up to 0.8% for Interdependent firms. This holds particularly for *big complex* firms whose performance is unequivocally the best in terms of *median growth* of value added, labor demand, and productivity, but much less impressive on *average*, especially concerning productivity growth, which is nil. But note that it is still far better than the other clusters, which display a *negative growth*.

The median of the distribution of performances of each cluster has experienced a generalized positive shift, with Complex firms moving with a higher “jump” (3.8%) when compared to the overall shift (1.8%). Indeed, more marked movements of the medians compared to the movements of the means stand for increases in the left-skewness of the distribution: even within clusters and within size classes, one observes polarizing tendencies. Given the generalized shift, Figure 3 plots deviations of the average changes and median shifts of labor productivities *from* the respective total value by size class. While median shifts of Complex firms (blue) are always positive, average changes are positive only for big Complex firms. At the opposite Essential firms (red) always record negative values both on average changes and median shifts. Small Interdependent (green) firms signal positive dynamism both on average and median values when compared among their similar peers in terms of size.

To further characterize firm clusters, we look at the association between clusters and dominant co-occurring practices. In this respect, we analyze the co-occurrences in the answers within each cluster, as can be observed in Figure 4 where each circular chart refers to a cluster—Essential, Managerial, Interdependent, and Complex in (a), (b), (c), and (d), respectively. By treating the

Table 5. Characteristics of firm clusters (small enterprises, 10–49 workers)

Cluster		Firm		Workers			Value added		Labor productivity (value added/workers)		Profitability (Mol/Revenues)[a]		Average salary (cost per employee)	
		N.	%	N.	%	Average	Total (Mln €)	%	Average (euros)	Coeff. of variation	Average (%)	Coeff. of variation	Average (euros)	Coeff. of variation
Cl_1	Essential	57,513	30.7	893,877	27.1	15.5	33,057.6	20.3	36,982	2.1	7.9	34.5	28,551.9	0.7
Cl_1	Managerial	70,509	37.7	1,229,414	37.2	17.4	59,054.9	36.2	48,035	1.1	8.4	56.1	33,125.7	0.4
Cl_3	Interdependent	45,376	24.3	881,117	26.7	19.4	51,414.3	31.6	58,351	1.3	8.8	2.7	37,437.6	0.4
Cl_4	Complex	13,697	7.3	296,762	9.0	21.7	19,395.3	11.9	65,357	1.7	9.6	45.7	41,077.9	0.6
	Total	187,095	100.0	3,301,170	100.0	17.6	1,62,922.1	100.0	49,353	1.5	8.6	40.5	33,795.1	0.5

[a]Mol: Gross operating margins.

Table 6. Characteristics of firm clusters (medium and large enterprises, over 50 workers)

Cluster		Firm		Workers			Value added		Labor productivity (value added/workers)		Profitability (Mol/Revenues)[a]		Average salary (cost per employee)	
		Number	%	Number	%	Average	Total (euros Mln)	%	Average (euros)	Coefficient of variation	Average (%)	Coefficient of variation	Average (euros)	Coefficient of variation
Cl_1	Essential	2867	11.6	388,952	6.9	135.7	14,312.4	3.8	36,797	1.3	4.8	975.4	31,217.7	0.7
Cl_1	Managerial	6531	26.5	876,651	15.6	134.2	44,761.6	11.8	51,060	1.7	6.3	19.1	36,802.3	0.6
Cl_3	Interdependent	8891	36.1	1,714,225	30.4	192.8	1,07,925.9	28.5	62,959	1.3	7.5	5.8	42,073.2	0.5
Cl_4	Complex	6373	25.8	2,650,565	47.1	415.9	2,11,978.0	55.9	79,975	1.3	10.2	0.0	50,672.1	0.4
	Total	24,662	100.0	5,630,394	100.0	228.3	3,78,977.9	100.0	67,309	1.3	8.7	184.0	44,273.6	0.5

[a]Mol: Gross operating margins.

Table 7. Dynamic performance of firm clusters (2016–2018)

		Value added		Turnover		Workers		Productivity	
		Average change	Median of change	Average change	Median of change	Average change	Median of change	Average change	Median of change
All sample									
Cl_1	Essential	5.1	8.6	4.8	6.9	5.4	7.0	−0.2	0.6
Cl_1	Managerial	10.5	9.0	13.1	8.8	9.8	6.4	0.6	1.7
Cl_3	Interdependent	12.9	11.6	13.4	11.2	12.0	7.2	0.8	2.5
Cl_4	Complex	9.9	15.9	11.8	16.8	9.6	9.7	0.2	3.8
	Total	10.5	10.1	12.0	9.5	9.8	7.1	0.6	1.8
Small enterprises (10–49 workers)									
Cl_1	Essential	3.2	8.6	3.1	6.8	2.4	7.0	0.7	0.5
Cl_1	Managerial	9.5	8.9	9.9	8.6	6.6	6.3	2.7	1.7
Cl_3	Interdependent	14.2	11.6	16.6	11.2	7.8	7.2	5.9	2.6
Cl_4	Complex	11.9	17.2	12.7	18.3	8.7	11.0	3.0	4.3
	Total	9.9	9.9	11.1	9.2	6.0	7.1	3.7	1.8
Medium and large enterprises (50+ workers)									
Cl_1	Essential	10.0	10.1	9.7	9.3	13.0	6.9	−2.7	1.2
Cl_1	Managerial	11.9	11.1	17.3	10.4	14.5	7.0	−2.3	1.6
Cl_3	Interdependent	12.3	11.6	12.0	11.5	14.1	7.1	−1.6	1.9
Cl_4	Complex	9.7	13.0	11.7	14.0	9.7	7.5	0.0	2.9
	Total	10.7	11.7	12.4	11.7	12.0	7.2	−1.1	2.0

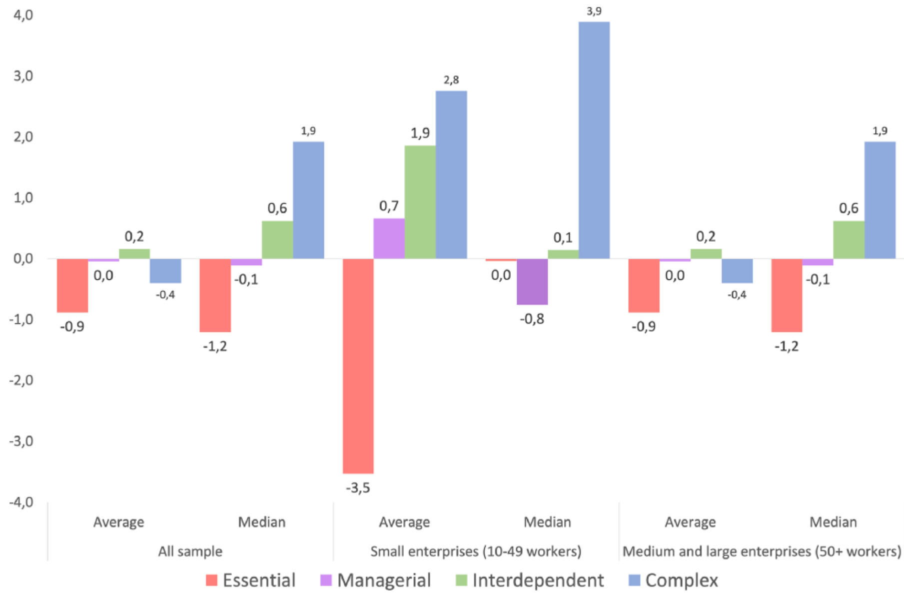

Figure 3. Deviations of average changes and median shifts of labor productivities from respective total values by size class

answers as independent events, for each firm cluster and each question, we look at the positive or negative response frequency of the firms in the cluster and select the answers shown in Figure 4 using a χ^2 test. Our null hypothesis is that the answers are equally distributed, determined only by the number of firms in each cluster.

The simultaneous significance of two or more answers determines the co-occurrence of questions in the circular charts. For each cluster, answers with the higher positive χ^2 tests (those with a greater discrepancy between the observed and theoretical frequency predicted by the null hypothesis) are displayed, and text size is proportional to the answer's significance. The selection of significant questions, i.e., the χ^2 cutoff for each cluster, is carried out with a heuristic approach, close to Elbow's method.

In line with the descriptive analysis presented in Figure 1, we detect greater diversification in the number of significant questions as the complexity of the clusters increases. Whereby Essential firms display a fundamental lack of any systematic organizational structure and strategic plans, i.e., few significant characteristics in almost every macro-area of the survey, with particular emphasis on the absence of current and future strategic objectives (e.g., no investments in R&D and human resources and defensive strategies in local markets), Complex firms appear to be characterized by the co-occurrence of the majority of practices meant to achieve technological and skills upgrading (4th Industrial Revolution, upskilling).

More in detail, Essential firms (Figure 4a) feature either low rates of current or future investment in innovative activities, R&D, digitalization and cybersecurity, or no investment at all, and human resources policies are mainly oriented toward cyber- and network security, while no process safety policy is undertaken. They are almost exclusively geared toward expanding the product/service range and domestic activities while pursuing defensive strategies. While still featuring low-capability diversification and no specific product or process safety strategy, Managerial firms (Figure 4b) rely to some extent on promoting external collaborations, accessing to new markets and attention to localization.

By contrast, Interdependent and Complex firms (Figure 4c and d) present more nuanced and structured profiles, are diversified in their wide-ranging strategies and, especially Complex ones, answer positively to the majority of the questions. Both clusters emphasize R&D, innovation, and different kinds of investments, with a large number of positive answers to the questions on a broad spectrum of workforce training activities and HR policies. Interdependent firms are often

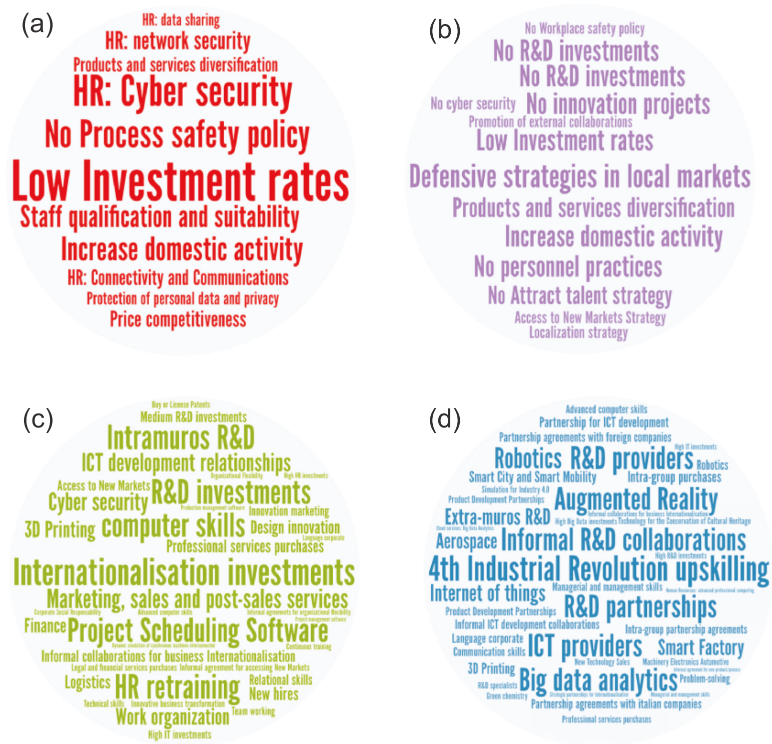

Figure 4. Co-occurrences of capabilities and strategies in each firm cluster identified in our analysis of the IMCPI questionnaire, with the main strategies of the firms belonging to the Essential, Managerial, Interdependent, and Complex clusters reported in (a), (b), (c), and (d), respectively

suppliers that operate mainly on order and are characterized by active market strategies as well as by active relations and partnerships with other local or international firms—primarily to provide services or management activities related to distribution, internationalization, marketing, and pre- and post-sales services. However, for what concerns training and human resources, they mainly focus on IT and cybersecurity, as well as linguistic and technical-organizational skills, staff retraining, work organization, and team working. Many strategies included in the “Interdependent” circle are related to relational features: marketing, sales and post-sales services, internationalization investments, professional services purchases, access to new markets, legal and financial services purchases, and logistics.

Conversely, what is most apparent for Complex firms are all characteristics linked to Industry 4.0, not only in terms of investments in digitalization and big data but also in terms of their main areas of specialization, e.g., smart city and mobility, smart factory, aerospace, and green chemistry. The training activities they carry out are mainly concerned with advanced computer skills, 3D printing, big data, robotics, simulation between interconnected machines, and augmented reality. Special attention is devoted to the acquisition of managerial and problem-solving skills, with HR policies especially focused on management and strategic planning. Moreover, Complex firms are also tightly connected with R&D and ICT-related activities, as well as with the development of new products and professional services.

Finally, the sectoral distribution of the different taxa is far from homogeneous. Figure 5 illustrates it within manufacturing and service sectors (2-digit aggregation level of Nace Rev. 2 codes), in terms of the number of firms and in Figure 6 in terms of share of value added. Those sectors that are defined as Supplier Dominated according to Pavitt (1984) taxonomy—such as apparel, leather goods, and textiles—are largely populated by Essential and Managerial companies; by

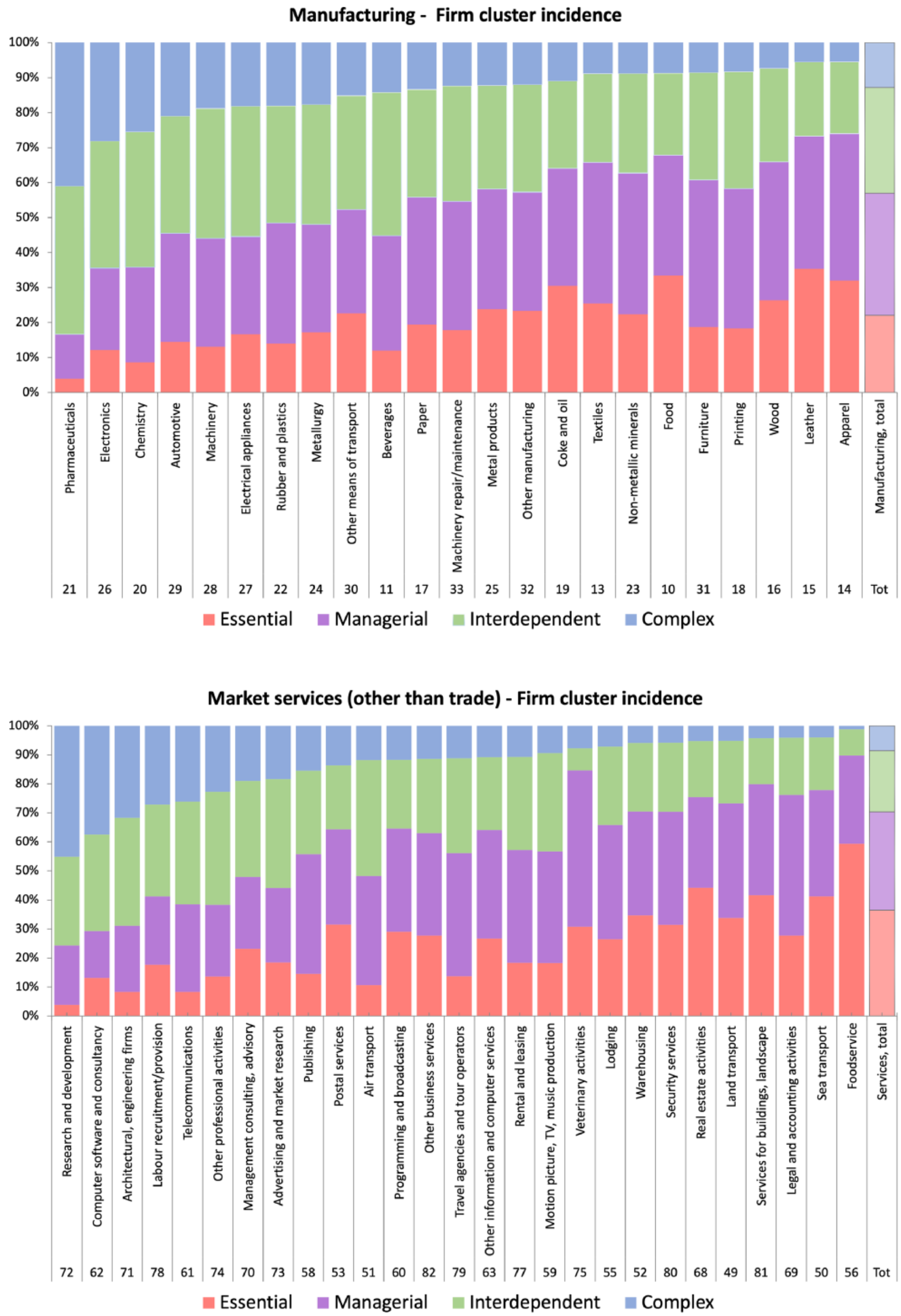

Figure 5. Incidence of firm clusters by economic activity sector (firms with at least 10 employees, percentage values) for manufacturing and service firms, respectively, in the upper and lower sections of the figure

contrast, those sectors (Science Based and a few Scale Intensive ones) with higher technological intensity and fast learning processes—such as pharmaceuticals and electronics—are largely populated by Complex firms. More in detail, in sectors 21-Pharmaceuticals, 26-Electronics, 20-Chemistry, and 29-Automotive, we observe a relative higher prevalence of firms belonging to the

Figure 6. Weight of the firm clusters in terms of value added, by sector of economic activity (units with at least 10 employees, percentage values), for manufacturing and market services firms, respectively, in the upper and lower sections of the figure

Complex cluster. In services, the Complex cluster prevails in most knowledge-intensive sectors: 72-Research and Development, 62-Information Technology, and 71-Engineering.

In terms of value added (Figure 6), the picture is more heterogeneous, with contributions ranging from the 40% to 70% of Complex firms. In manufacturing, the weight in value added of the Complex cluster is particularly high in Scale Intensive and Specialized Supplier sectors, such as 30-Other means of transport (above 80%), 29-Automotive (74%), 27-Electrical appliances, and 26-Electronics (60% in both), notwithstanding a relatively low share in terms of numbers (around

20% in both). Within services, a greater polarization emerges: in some knowledge-intensive activities, the Complex cluster accounts for almost all value added, e.g., 53-Postal services and 61-Telecommunications, and for a share not lower than two-thirds for 60-Programming and broadcasting, 72-R&D, 62-ICT, and 74-Other professional activities. In other market services such as 68-Real estate, 80-Security, and 77-Housing, which are quite relevant in terms of the number of firms and employment levels, the share of value added belonging to the Complex units is around 10%.

The sectoral analysis also highlights that Managerial firms tend to exhibit sectoral frequencies more similar to the Essential ones, while Interdependent firms tend to move alike those in the Complex cluster, in terms of both shares of value added and of number of firms.

5. Estimation strategy

In order to detect more precisely the extent to which firm performances are linked to membership in one of the four clusters, we use some econometric models connecting the dynamics of firm productivity and employment to its organizational profile. More in detail, we start by estimating a cross-sectional linear regression model:

$$\pi_{i,t} = \alpha_1 + \alpha_2 Cl_{k,2018} + \alpha_3 X_{i,2016} + \gamma + \delta_{i,t} + \epsilon_{i,t} \quad k = 1, \ldots, 4 \quad t = 2019, 2020 \tag{1}$$

where $\pi_{i,\,t}$ represents log labor productivity (in terms of value added per worker) in 2019 and 2020, α_1 is the constant term, $Cl_{k,2018}$ are the dummy variables for the four clusters in 2018, $X_{i,2016}$ is a vector of firm-level control variables in 2016, including size, level of human capital (measured by two variables: average years of schooling of employees and tenure of employees), age of the firm (measured by the logarithm of years of activity), profitability (calculated as the ratio between gross profit margins and sales), export propensity (in terms of the logarithm of the share of export on turnover), and three dummy variables on being part of a business group (domestic group, multinational group with domestic control, and multinational group with foreign control, respectively). Finally, γ and δ are dummy variables controlling for sectoral (2-digit Nace Rev.2 level) and geographical (NUTS 1 level) effects, respectively. The estimation is first carried out for the whole sample and then repeated for small, medium, and large enterprises, in order to take into account the size dimension.

The results are reported in Table 8. With respect to the all-sample estimation, we detect a positive and significant effect of belonging to each of the three "advanced" clusters vis-a'-vis the Essential baseline on the level of labor productivity in both 2019 and 2020. The magnitude is remarkable, ranging from 5% to 13%, notably increasing along clusters, with Complex firms having an advantage in labor productivity of approximately 13% with respect to Essential firms in 2019 and nearly 14% in 2020 when the COVID-19 pandemic deeply affected the business environment. Note that in our case, the lagged structure between firm clusters and productivity dynamics appears sufficient to avoid reverse causality in the estimate, due to the peculiar characteristic of the COVID-19 crisis: this was completely exogenous to the business system and therefore totally unpredictable for the firms, so that we can reasonably assume that none of the strategies we considered in our estimate—pursued in 2018—is in any case affected by the 2020 level of performance. As a consequence, we can deem that the parameters of our model are unbiased estimations of the influence of the belonging to a cluster on the firm performance. There might be however a composition effect due to the firm size. When replicating the estimates by size class, we continue to find that for small-sized enterprises techno-organizational complexity is associated with higher levels of labor productivity in 2019 and 2020, even if with relatively smaller differences in the magnitude of the elasticity compared to the all-sample estimation. Among medium-sized firms, the effect is still positive and significant in 2019 for Interdependent and Complex firms—even though the magnitude is lower—while no significant differences are detectable between Essential and Managerial firms. In 2020, only the Complex firms show labor productivity levels significantly higher than the Essential ones. Finally, for large firms, belonging to any cluster does not seem to have any effect on productivity levels either in 2019 or in 2020.

Table 8. Linear regression estimation of Equation (1). Dependent variable: labor productivity (2019, 2020)

	All sample		Small (10–49 workers)		Medium (50–249 workers)		Large (250+ workers)	
	2019 (1)	2020 (2)	2019 (3)	2020 (4)	2019 (5)	2020 (6)	2019 (7)	2020 (8)
Managerial_{2018}	0.058***	0.042*	0.067***	0.041*	0.035	0.010	−0.161	−0.079
	(0.018)	(0.022)	(0.017)	(0.021)	(0.032)	(0.035)	(0.187)	(0.118)
$\text{Interdependent}_{2018}$	0.104***	0.107***	0.114***	0.107***	0.059*	0.035	−0.086	−0.023
	(0.017)	(0.022)	(0.018)	(0.023)	(0.032)	(0.035)	(0.187)	(0.114)
Complex_{2018}	0.129***	0.137***	0.131***	0.138***	0.099***	0.063*	−0.018	0.001
	(0.019)	(0.024)	(0.020)	(0.027)	(0.033)	(0.035)	(0.187)	(0.116)
Size_{2016}	0.049***	0.103***	0.109***	0.166***	0.009	0.018	−0.025	0.002
	(0.005)	(0.008)	(0.010)	(0.016)	(0.012)	(0.016)	(0.017)	(0.030)
Schooling_{2016}	0.932***	0.793***	0.848***	0.759***	1.421***	1.324***	1.843***	1.485***
	(0.054)	(0.066)	(0.045)	(0.068)	(0.058)	(0.078)	(0.145)	(0.208)
Tenure_{2016}	0.087***	0.065***	0.068***	0.044***	0.103***	0.088***	0.132***	0.176***
	(0.010)	(0.016)	(0.011)	(0.014)	(0.013)	(0.014)	(0.028)	(0.041)
Age_{2016}	0.007	0.014	0.005	0.011	0.014	0.013	0.008	0.015
	(0.008)	(0.011)	(0.010)	(0.012)	(0.009)	(0.010)	(0.018)	(0.027)
$\text{Profitability}_{2016}$	1.318***	1.238***	1.572***	1.398***	1.299***	1.216***	1.781***	1.071**
	(0.081)	(0.101)	(0.083)	(0.132)	(0.162)	(0.211)	(0.444)	(0.460)
Exporting_{2016}	0.024***	0.015**	0.025***	0.013**	0.017***	0.018***	0.020	0.024
	(0.003)	(0.006)	(0.003)	(0.006)	(0.004)	(0.005)	(0.012)	(0.020)
DomesticBG_{2016}	0.148***	0.177***	0.152***	0.169***	0.071***	0.075***	0.037	−0.023
	(0.010)	(0.014)	(0.011)	(0.016)	(0.013)	(0.015)	(0.052)	(0.062)
$\text{MultinationalBG1}_{2016}$	0.307***	0.385***	0.360***	0.420***	0.192***	0.256***	0.126**	0.064
	(0.017)	(0.029)	(0.021)	(0.043)	(0.019)	(0.023)	(0.050)	(0.067)
$\text{MultinationalBG2}_{2016}$	0.206***	0.215***	0.221***	0.245***	0.126***	0.101***	0.117**	−0.002
	(0.013)	(0.018)	(0.016)	(0.027)	(0.014)	(0.018)	(0.051)	(0.065)
Sector controls_{2016}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geography controls_{2016}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8.246***	8.252***	8.277***	8.172***	7.260***	7.353***	6.138***	6.787***
	(0.141)	(0.178)	(0.121)	(0.177)	(0.160)	(0.233)	(0.421)	(0.568)
Observations	55,163	45,885	38,552	33,564	12,178	9259	2278	1156
R^2	0.320	0.282	0.310	0.246	0.304	0.321	0.445	0.475

*$P<0.1$; **$P<0.05$; ***$P<0.01$. Robust standard errors in parenthesis. Essential firms are the benchmark group.

In other words, size and complexity tend to mix with each other when size increases, while complexity remains very much relevant for small and medium firms. Distinguishing size vs complexity is indeed an exercise that allows us to go beyond the sheer effect of the former and to investigate the relevance of the behavioral traits.

The introduction of a large set of firm-level controls (referred to 2016), usually considered in the literature as potential determinants of labor productivity, reassures us about omitted variable problems (and the very small values of the Variance Inflation Factor test, always well below 3%, reassure us against overspecification issues). Notably, the variables related to firms' financial resources (profitability), workers' schooling and length of tenure are all associated with a higher level of labor productivity 3 and 4 years later, also in line with the conspicuous strand of literature emphasizing the role of workers' abilities in fostering firm productivity (Dosi *et al.*, 2021). Firm size has also a positive effect along the same time span, but only among small units, losing significance for medium and large firms, while export propensity correlates with labor productivity for all SMEs. Finally, belonging to a group appears to be positively associated with labor productivity, and (especially for large enterprises) when the group is a multinational one, no matter whether it is under domestic or foreign control.

Table 9. OLS estimation of Equation (2) and multinomial logit estimation of Equation (3)

	OLS	Multinomial logit			
	Dep. Var:	Dep. Var: productivity and employment change (2018–2020)			
	Productivity change 2018–2020	ΔEmpl ≤ 0 Δprod ≤ 0	ΔEmpl > 0 Δprod ≤ 0	ΔEmpl ≤ 0 Δprod > 0	ΔEmpl > 0 Δprod > 0
	(1)	(2)	(3)	(4)	(5)
Managerial_{2018}	−0.003	−0.012***	0.033***	−0.001	−0.019***
	(0.018)	(−0.004)	(−0.004)	(−0.004)	(−0.004)
$\text{Interdependent}_{2018}$	0.020	−0.048***	0.067***	−0.031***	0.013***
	(0.017)	(−0.005)	(−0.005)	(−0.004)	(−0.004)
Complex_{2018}	0.038**	−0.079***	0.087***	−0.045***	0.038***
	(0.018)	(−0.006)	(−0.006)	(−0.005)	(−0.005)
Small_{2016}	0.031	0.018***	−0.023***	−0.020***	0.026***
	(0.029)	(−0.005)	(−0.006)	(−0.005)	(−0.004)
Medium_{2016}	0.097***	−0.031***	−0.073***	0.026***	0.077***
	(0.029)	(−0.007)	(−0.007)	(−0.006)	(−0.006)
Large_{2016}	0.110***	−0.069***	−0.172***	0.134***	0.107***
	(0.033)	(−0.012)	(−0.011)	(−0.012)	(−0.011)
$\text{Productivity}_{2016}$	0.039**	−0.114***	0.032***	0.012***	0.070***
	(0.018)	(−0.004)	(−0.004)	(−0.003)	(−0.003)
Schooling_{2016}	−0.138***	−0.019	0.079***	−0.076***	0.017
	(0.053)	(−0.015)	(−0.015)	(−0.013)	(−0.013)
Tenure_{2016}	−0.034***	0.042***	0.012***	−0.005*	−0.048***
	(0.012)	(−0.003)	(−0.003)	(−0.003)	(−0.003)
Age_{2016}	0.018**	0.024***	−0.016***	−0.007***	−0.002
	(0.009)	(−0.003)	(−0.003)	(−0.002)	(−0.002)
$\text{Profitability}_{2016}$	−0.324***	0.392***	0.273***	−0.255***	−0.410***
	(0.068)	(−0.021)	(−0.021)	(−0.017)	(−0.017)
Exporting_{2016}	−0.011**	0.005***	−0.007***	0.003***	−0.001
	(0.005)	(−0.001)	(−0.001)	(−0.001)	(−0.001)
DomesticBG_{2016}	0.028**	−0.019***	−0.017***	0.015***	0.022***
	(0.013)	(−0.004)	(−0.004)	(−0.003)	(−0.004)
$\text{MultinationalBG1}_{2016}$	0.078***	−0.039***	−0.097***	0.095***	0.042***
	(0.024)	(−0.007)	(−0.007)	(−0.007)	(−0.006)
$\text{MultinationalBG2}_{2016}$	0.032*	−0.058***	−0.042***	0.053***	0.048***
	(0.017)	(−0.006)	(−0.006)	(−0.006)	(−0.005)
Geography controls	Yes	Yes	Yes	Yes	Yes
Sector controls	Yes	Yes	Yes	Yes	Yes
Observations	45,627	56,818	56,818	56,818	56,818
R^2 (column 1)/pseudo_R^2	0.0715	0.0522	0.0522	0.0522	0.0522

OLS: Dep. Var is the percentage change of productivity in 2018–2020. Multinomial logit: dependent variable is a categorical variable taking value 1 for (ΔEmpl ≤ 0, Δprod ≤ 0); 2 for (ΔEmpl > 0, Δprod ≤ 0); 3 for (ΔEmpl ≤ 0, Δprod > 0); and 4 for (ΔEmpl > 0, Δprod > 0). Marginal effects are reported.
$^*P < 0.1$; $^{**}P < 0.05$; $^{***}P < 0.01$. Robust standard errors. Essential firms are the benchmark group.

To better grasp the effects of the capability clusters, we estimate three further linear models, with reference to firm productivity *changes* in the three-year period 2018–2020, with covariates expressed at 2016 levels:

$$\Delta\pi_i = \alpha_1 + \alpha_2 Cl_{k,2018} + \alpha_3 X_{i,2016} + \gamma + \delta_i + \epsilon_i \quad k = 1, \dots, 4 \tag{2}$$

where $\Delta\pi_i$ represents the percentage change in firm productivity in 2018–2020, α_1 is the constant term, Cl_k are dummies indicating the belonging to the four clusters, and X_i is the same vector of firm-level control variables as in Equation (1).

The results are reported in Table 9 (column 1). Once we consider productivity changes, belonging to the Complex group is accompanied by higher increases in labor productivity (+3.8%), while for the other clusters, there are no significant differences. However, increases in productivity might come at the cost of labor expulsion or, on the contrary, might coexist with labor absorption. The two are clearly opposing organizational strategies that the firm might face. Conversely, productivity might decrease together with labor expulsion or coexist with labor hoarding.

Thus, we ought to distinguish the four potential outcomes linking productivity and employment changes to detect the differences in terms of these alternative scenarios across the different clusters. To do so, we estimate the effect of belonging to each of the four clusters on the probability of the occurrence of the following four scenarios of firm growth/contraction in the period 2018–2020:

1. decrease (or stagnation) in employment (number of workers) and in labor productivity;
2. increase in employment and reduction (or stagnation) in productivity;
3. reduction (or stagnation) in employment and increase in productivity; and
4. increase in both employment and productivity.

In this regard, since the belonging of each firm to the different profiles is expressed through a qualitative variable that has a finite number of modalities without an evident ordering (nominal polytomous variable), we estimate a multinomial logit model,[5] which in our case takes the following specification:[6]

$$Pro\left(Y_i = j \vee Cl_{k,2018}, X_{i,2016}\right) = \frac{\exp\left(\alpha_{ij} + Cl_{k,2018}\beta_{ij} + X_{i,2016}\gamma_{ij}\right)}{1 + \sum_{m=2}^{J}\exp\left(\alpha_I + Cl_{k,2018}\beta_I + X_{i,2016}\gamma_I\right)} \tag{3}$$

where

- Y_i is a categorical variable relating firm *i* to one of the four scenarios of employment and productivity dynamics previously described, taking the value 1 for Empl ≤ 0, Δprod ≤ 0; 2 for ΔEmpl > 0, Δprod ≤ 0; 3 for ΔEmpl ≤ 0, Δprod > 0; and 4 for ΔEmpl > 0, Δprod > 0;
- $Cl_{k,2018}$ is a vector of the usual four dummy variables referring to the clusters;
- $X_{i,2016}$ is the vector of usual firm-level control variables in 2016.

The marginal effects of each covariate (the four clusters), i.e., their contribution to the probability of having experienced a given scenario of labor and productivity dynamics, are reported in Table 9 (columns 2–5). First, the multinomial model confirms that a greater technological-organizational complexity is associated with a higher probability of experiencing growth in both outcomes. As compared to the Essential baseline, belonging to any other cluster reduces the probability of having experienced, in the period 2018–2020, a reduction in both employment and productivity, with differentials ranging from −1.2 percentage points for Managerial firms to about −8% for Complex (column 2).

The case of labor hoarding associated with an apparent decrease in labor productivity (column 3), possibly due to an increase in employment higher than that of value added, records a mirroring dynamics: when compared to the Essential firms, all other clusters register a positive probability differential in the range between +3.3% and +8.7%. This result implies that in the baseline Essential firms, productivity losses tend to be more closely associated also with the expulsion of the labor force.

Conversely, productivity growth at the cost of employment (column 3) is a strategy relatively infrequent in Complex and Interdependent firms: belonging to these clusters reduces the probability of increasing productivity at the cost of (and partly through) a reduction in employment (−3.1 and −4.5%, respectively).

[5] This type of models allows us to estimate the effect of a vector of explanatory variables of interest (***x***) on the probability of observing each outcome, $Prob\left(y = j \vee x\right)$, *j* = 2,…, *J*. Since the sum of the probabilities is unitary, it follows that $Prob\left(y = j \vee x\right)$ is known once the probabilities for the remaining modes (*j* = 2,…,*J*–1) are known. Letting *j* = 1 be the reference category, the probability of *j* = *i* is therefore given by $Prob\left(y = j \vee x\right) = \frac{\exp(x\beta_i)}{1+\sum_{m=2}^{J}\exp(x\beta_m)}, j > 1$, where x is a vector of explanatory variables and β_m is the vector of parameters for the type *m* (*m* = 2,…, *J*).

[6] In our exercise, the choice of the multinomial model is supported by empirical evidence for the hypothesis of parallel regressions (Independence from Irrelevant Alternatives [IIA]). IIA is verified by data. Furthermore, the Wald test allows us to reject the null hypothesis of joint non-significance of the parameters associated with each explanatory variable. Finally, the test on combinations of modes of the dependent variable rejects the null hypothesis about the existence of pairs of categories that are not significantly different from the explanatory variables of the model.

Table 10. Incidence of four scenarios of productivity and employment dynamics, by cluster (% of firms)

Cluster	ΔEmpl ≤ 0 Δprod ≤ 0	ΔEmpl > 0 Δprod ≤ 0	ΔEmpl ≤ 0 Δprod > 0	ΔEmpl > 0 Δprod > 0	Total
		2018–2020			
Essential	36.5	20.9	21.7	20.9	100.0
Managerial	32.4	27.1	21.7	18.8	100.0
Interdependent	27.1	30.1	19.7	23.1	100.0
Complex	20.0	30.3	19.8	29.9	100.0
Total	31.0	26.4	21.0	21.6	100.0
		2018–2019			
Essential	19.2	21.3	35.5	24.0	100.0
Managerial	17.3	25.3	30.9	26.5	100.0
Interdependent	16.0	28.6	25.8	29.6	100.0
Complex	14.3	30.8	21.5	33.4	100.0
Total	17.2	25.6	30.0	27.2	100.0
		2019–2020			
Essential	40.8	19.7	19.7	19.8	100.0
Managerial	38.5	24.3	20.1	17.1	100.0
Interdependent	33.0	27.7	19.5	19.8	100.0
Complex	25.2	29.1	21.3	24.4	100.0
Total	36.5	24.3	20.0	19.2	100.0

Finally, the scenario in which firms are able to expand in both dimensions, that is making processes more efficient but also employing more workers, is more probable in the two upper clusters (+1.3 and +3.8%, respectively), while the Managerial cluster records negative probabilities when compared to the Essentials (–1.9%).

From this last battery of analyses, we conclude that being characterized by a higher technological-organizational complexity tends to be associated with a double-positive performance in terms of both increasing productivity and employment. On the opposite hand, productivity slowdown associated with employment reduction is largely attributable to the Essential, most numerous, cluster.

Table 10 illustrates the incidence of the four outcomes across clusters.

- In the three-year period 2018–2020, nearly one-third of Italian firms experienced a contraction in both productivity and employment, while about one-fifth grew on both variables.
- Productivity slowdown affected over 57% of firms (about 121,000 units), which were mostly Essential and Managerial firms (about 80,000).
- Among Essential and Managerial enterprises, the incidence of cases of general contraction (scenario 1) reaches the highest values, while Complex ones tend to display mostly scenarios of labor hoarding (scenario 2) or productivity and employment growth (scenario 4).
- In the pre-pandemic period (2018–2019), a reference point, the contribution of Essential and Managerial units to productivity dynamics, even when positive, prevalently came to the detriment of employment, contrary to Complex ones.
- In the COVID-dominated period (2019–2020), decreases in productivity and employment involved the relative majority of Essential, Managerial, and Interdependent firms. In that phase, Complex firms reacted with a variety of strategies, almost one-fourth reducing both employment and productivity and approximately another fourth expanding in both directions.

6. Conclusions

Identifying organizational capabilities is a daunting task, as it necessarily requires the search for relatively invariant behavioral traits, structures, and routinized procedures, that distinguish one firm from the other even within the same narrow domain of activities and lines of production.

To this end, in this work, we have proposed a novel empirical strategy, relying upon a rich informative source, the multi-purpose questionnaire designed by the ISTAT in 2019 as part of a firm permanent census helping to identify what we have called the *quasi-genetic traits of organizations*. By using this newly integrated database, we have developed a taxonomy of the Italian firms capable of mapping organizational structures, routines, and heuristics into different indicators of economic performance, in this work primarily labor productivity.

Such exercise fundamentally entails the identification of the *complementarities* across different practices. Hence, a first novel advancement of this work follows: by means of a factor analysis, we are able to distinguish discrete *taxa* based on the structural and behavioral identities of the firms. These profiles are primarily characterized by learning processes implemented on the grounds of a sort of "technological substratum"—e.g., investments in digitalization, business management software, and platforms adoption—and by a complementary set of organizational practices—ranging from staff training processes and career advancement systems to selection of skills required from newly hired personnel.

The role of managerial strategies *strictu sensu*—i.e., as detailed earlier, everything that pertains exclusively to managerial functions, such as defining outlet markets, product quality, and pricing mechanisms—emerges only as a second-order set of determinants. Finally, company's positioning with respect to a system of relations—both externally in terms of value chains and internally in terms of workforce safety and welfare—represents a further element that contributes to explaining the high degree of heterogeneity observed among different firms.

We identified four clusters of firms called *Essential, Managerial, Interdependent*, and *Complex*. Firms in the first two cluster tend to show characteristics similar to each other, while Interdependent firms in the third cluster are closer to those in the Complex one. In general, the identified taxa, we suggest, are a promising way to operationalize the notion of organizational capabilities as *distinctive* and *persistent* ensembles of organizational behaviors able to account also for persistently different performances.

The frequency distribution of each taxon, at least in the Italian case, is in line with the empirical literature that emphasizes the emergence of a neo-dualism (Dosi *et al.*, 2012, 2021), even within manufacturing, due to the presence of a relatively small core endowed with complex organizational practices—together with relatively high labor productivity, wages and profit margins—and a large fringe with opposite characteristics. Regression results corroborate the descriptive classification and highlight the importance of such intrinsic "genotypes" in affecting both productivity and employment growth conditional to the belonging to different clusters. Indeed, our evidence clearly shows that the productivity slowdown is largely imputable to a large fraction of lagging-behind firms that both in pre-pandemic and pandemic times tended to be mostly characterized by the higher incidence of productivity losses accompanied by employment ones. Such clusters (the Essential and Managerial firms) do represent two-thirds of the firms (nearly 80,000) out of all firms experiencing a productivity slowdown in the 2018–2020 period (nearly 121,000). This evidence clearly points at the roots of productivity slowdown stemming from a composition effect of a deeply dualistic industrial structure.

The perspective bears far-reaching implications for both business analysis and public policy. Concerning the former, it might well be futile to search for *the one best practice*, or, in analogy with economists' production theory, for the contribution of each individual practice (often equated to a resource) to some overall production function. Rather, it might be much more useful to detect the properties of different *combinatorics of practices*. In this respect, the contribution of, e.g., Fujimoto (1999) concerning the origins and ingredients of "Toyotism", has been a path-breaking archetype. Nowadays, with the availability of census-type information on corporate structures, behaviors, and strategies, it is possible to replicate the spirit of that classic study on a massive scale, even if, of course, at a much lower depth.

The implications in terms of policy are equally far-reaching. If our analysis is correct, the policy emphasis should be on the processes of learning and accumulation of techno-organizational capabilities. Thus, in the case we have analyzed—Italy—tackling the productivity stagnation crucially implies fostering the transition of those firms placed in the lower-capability clusters—the majority of Italian firms—forward on the ladder.

Finally, concerning future venues of research, the very robustness of our results hints also at their limitations. Indeed, our capability taxa appear to be so robust that they hold across sectors of manufacturing and services. However, the analysis must get deeper and identify finer properties of organizational capabilities that are sector- and technology-specific. After all, designing and building automobiles is very different from making semiconductors, or pharmaceutical products, or coding software. This, we believe, is the further frontier for the empirical analysis of organizational capabilities.

Supplementary Data

Supplementary data are available at *Industrial and Corporate Change* online.

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